Patent portfolio diversity and firm profitability:

A question of specialization or diversification?

Abstract

The relationship between patent portfolio diversity and firm profitability is conceptually opaque and empirically equivocal. We contribute to the literature with a systematic analysis of this relationship by carrying out an empirical investigation based on a sample of 391 international firms. We generate data for patent portfolio diversity at the level of sections, classes, and sub-classes of the International Patent Classification. As moderators of this relationship, we test non-self forward citations (revealing a stream of knowledge between the firm and the outside) and non-self backward citations (assessing the firm's absorptive capacity). Findings highlight how the relationship between patent portfolio diversity and profitability is non-linear and differentially moderated by both the level of non-self forward and backward citations. Accordingly, implications for theory development and managerial decision making are discussed.

Keywords: patent portfolio; diversity; performance; forward citations; backward citations

1. Introduction

Over the last two decades, scholars and practitioners have witnessed significant growth in patent applications worldwide (OECD, 2015). Though patenting firms can establish a competitive advantage and reinforce their market position (Blind et al., 2009; Meyer and Subramanian, 2014), patenting remains an expensive practice for firms, whose pre-grant and post-grant costs (de Rassenfosse & van Pottelsberghe de la Potterie, 2013) may exceed its potential benefits: the former, entailing claim-based or page-base fees, and application fees like agents' and translation ones (Harhoff et al., 2009); the latter, dealing with validation fees, yearly renewal fees, and all the costs to detect imitation and patent infringement (Parchomovsky & Wagner, 2005; Somaya, 2012). Other negative aspects (not only cost-related) emerge in cases in which the invention is easy to reverse engineer (Samuelson & Scotchmer, 2002) or the ease of inventing around makes it vulnerable in the face of the competition (Blind et al., 2009). In those cases, options such as secrecy and lead time prevail over patents to protect innovation (Cohen et al., 2000).

On the one hand, holding patents can endow a competitive advantage, support managers in R&D and technological investment decisions (Lai et al., 2015), and reinforce the firm's market position (Blind et al., 2009). However, on the other hand, the necessary investment to achieve and maintain patent protection are significant and the decision becomes one of an *ex ante* strategic decision based on the trade-off between benefits and costs of intellectual property rights (de Rassenfosse & van Pottelsberghe de la Potterie, 2013). Therefore, returns on patent investments may be low and, in most cases, difficult to estimate. Also, uncertainty in evaluating the value of patents *ex ante* is high, and it is linked to the technological and economic risks of the underlying invention. This line of reasoning indicates patents exhibit intrinsic value although some scholars argue the contrary where they have no value whatsoever (Parchomovsky & Wagner, 2005;

Shankerman, 1998). Although this asynchronous view on patent value and the existence of alternative ways of protecting technologies prevails, firms increasingly continue to increasingly make patent applications: United States Patent and Trademark Office (USPTO) registered 589,410 applications and granted 298,407 patents in 2015 only. This contradiction is known as the patent paradox and goes as follows: *if patents on inventions have little or no expected economic value, why do individuals and commercial corporations patent so heavily? Or, if patents are valuable after all, where does their value lie?* (Parchomovsky & Wagner, 2005, p. 5).

Parchomovsky & Wagner (2005) address this issue by considering patent portfolios instead of independent unitary patents in isolation. The justification to consider the patent portfolios as the unit of analysis is twofold. First, and being grounded in traditional finance (portfolio) theory (Jacobs & Swink, 2011), risk reduction can be clearer by understanding compensative effects: a negative trend of a common stock could be “balanced out” by a positive trend of another negatively related common stock; so, the total portfolio risk is less than the simple sum of single risks. Second, by relying on the concepts of synergy, considering a collection of patents as an integrated whole allows the value of a portfolio to become greater than the sum of the value of its single elements, thanks to the creation of synergies between elements (Lin et al., 2006). This twofold logic offers a rationale for investing in patent portfolios with varying degrees of diversity. Particularly, patent portfolio diversity can be defined as the extent to which patents are spread across technological fields. We follow the International Patent Classification (IPC) which is a hierarchical classification system divided into sections, classes, and sub-classes. However, existing literature shows opposing views on whether portfolio diversity is beneficial for firm performance, and empirical research has been so far limited and anecdotal.

We aim to shed new light on the patent paradox by investigating the impact of patent portfolio diversity on the profitability of firms operating in patent-intensive manufacturing industries. We also explore how this relationship is attenuated when two important moderators are considered: non-self forward citations (FCs) (Hall et al., 2005; Yang et al., 2010; Grimaldi et al., 2015) and non-self backward citations (BCs) (Cohen & Levinthal, 1990; Zahra & George, 2002).

Our paper is explicated as follows. We continue by introducing portfolio management strategy and discuss specialization-diversification dilemma. Thereafter, we propose a research framework with three hypotheses. Then we describe our research design, methods, and results. Finally, we conclude with a discussion of the theoretical and managerial implications, limitations and avenues for future research.

2. THEORETICAL BACKGROUND

Portfolio management decisions are critical strategic decisions, which depend on several factors such as the firm's characteristics, industry, and competitors' behaviors (Blind et al., 2009; Fernhaber and Patel, 2012; Hall et al., 2005; Somaya, 2012). A patent portfolio may: first, be used to make sense of the management of technological resources (Ernst, 2003); second, enable companies to assess their competitive positioning within specific technological fields (Lin et al., 2006); third, unleash 'offensive races' in which few firms coordinate to gain competitive advantage (Jell et al., 2017); and, finally, help firms to study the evolution of technology within markets (Grimaldi et al., 2015). Overall, through the exploitation of bundles of technological resources, a better positioning facing increasing competition, and an increased capability to foresee technological change, patent portfolios can have a strong and robust effect on firms' profitability (Czarnitzki and Kraft, 2010; Pohlmann et al., 2016). Accordingly, patenting can be conceived of as a profit maximizing strategy since it can lead to sales revenue maximization or cost reduction

(Van-Triest and Vis, 2007), regardless of whether firms carry out their business in developed or developing countries (Ambrammal and Sharma, 2016; Graphar et al., 2014). The way profitability is derived depends on the patent portfolio strategy the firm decides to follow.

Two major alternative patent portfolio strategies have been identified to enable profitability gains. These are *patent portfolio specialization* and *patent portfolio diversification*. By following a patent portfolio specialization strategy, a firm decides to focus its efforts on core competencies which are shared by across all the portfolio's constituent elements. Specialization allows firms to stand out due to their deep knowledge of their field, laying the foundations for a strong competitive advantage (Lin et al., 2006). It is also a way to benefit both from economies of experience associated with learning processes and the easier knowledge exchange between core technologies (Garcìa-Vega, 2006). This strategy is linked to incremental inventions grounded in existing knowledge and core competencies (Quintana-Garcìa & Benavides-Velasco, 2007). Parchomovsky & Wagner (2005) underline that a firm's patent portfolio should be narrowly focused in a technological field, creating the premises for a 'super patent' that creates a superadditive right to exclude others from innovating in a broader technology set and gives the firm a stronger bargaining power position in a specific field. Breschi et al (2003) define specialized innovators firms that operate in only one technological field. The major risk for these firms is that of remaining locked in an obsolete field without the ability to change and renew their business (Quintana-Garcìa & Benavides-Velasco, 2007).

In contrast, by pursuing a patent portfolio diversification strategy firms increase the scope of their activities by adding elements with characteristics that are not homogeneous. This means extending the knowledge system and principles underlying their products and their methods of production (Garcìa-Vega, 2006; Leten et al., 2007). A firm can decide to pursue a technological diversification strategy because of several reasons including the: availability of slack resources; to exploit learning economies; to manage high uncertainty of research and development and broader innovation activities; and, the development of new, risky technologies or increasing the complexity of products and process (Leten et al., 2007; Garcìa-Vega, 2006). These drivers are industry-specific and path dependent, yet technological diversification can bring several benefits to firms.

From a financial portfolio standpoint, diversification allows risk pooling (Garcìa-Vega 2006). In general, this strategy allows firms to exploit new opportunities offered by the market (Garcìa-Vega, 2006; Lin et al., 2006) thereby broadening firms' horizons in order to prevent market lock-in. Indeed, diversification allows firms to better explore and understand the commercial potential of the technology and so to co-evolve with the market (Chen et al., 2013; Garcìa-Vega, 2006). Through technological diversification, unexpected cross-fertilizations of knowledge can emerge: the combination of different technologies could generate successful and revolutionary innovations (Chen et al., 2013). However, diversification is never costless. Diversification entails investments allowing firms to explore new technological fields (Quintana-Garcìa and Benavides-Velasco 2007). An excessive technological diversification (over-diversification trap) causes a strong increase in coordination, communication, and technological knowledge integration costs (Chen et al., 2013; Lin et al., 2006). It may also nullify the benefits of a portfolio because unrelated patents can be placed in sparse technological fields that can cause a reduction in competitive power and protection (Parchomovsky & Wagner, 2005).

3. HYPOTHESIS DEVELOPMENT

3.1 Patent portfolio diversity and firm profitability

Increasing patent portfolio diversity can have positive effects on firm profitability for a number of reasons. First, it allows risk pooling whereby the total risk of a portfolio is less than the risks of single patent investment. This enables firms to incur more investments in order to exploit more opportunities, and at the same time, it allows taking fewer risks. Second, a diversified portfolio enhances a firm's capability to recognize new, successful opportunities. Indeed, the combination of different technologies contributes to creating new inventions (Chen et al., 2013; Garcìa-Vega, 2006; Leten et al., 2007; Lin et al., 2006; Quintana-Garcìa & Benavides-Velasco, 2007). For instance, combining multidisciplinary knowledge from electronics, mechanics, and informatics led to the development of mechatronics, a distinct and burgeoning engineering sector (Leten et al., 2007).

Diversity has a positive effect on innovative ability, with a higher influence on exploratory innovative competence—that is the firm's ability to create new technologies by linking different knowledge (Quintana-Garcìa & Benavides-Velasco, 2007). Therefore, diversity provides firms to better fulfill markets expectations and to potentially generate breakthrough innovations (Kaplan & Vakili, 2014). Notwithstanding its value, diversity does not come without its own challenges which include significant outlays in order to sustain knowledge development and coordination and communications costs (Chen et al., 2013; Parchomovsky & Wagner, 2005). High degrees of patent portfolio diversity can weaken a firm's market position where patents spread across too many technology fields do not guarantee the good protection of inventions or success (Parchomovsky & Wagner, 2005). However, some scholars have demonstrated that increasing diversity may have some further potential downsides that include trade-offs between diversity and transaction costs, rather than having difficulties in coordinating and frequently re-adapting organizational routines (Stirling, 2007). A moderate level of technological diversity seems to be the ideal solution

(Sampson, 2007). Beyond a certain threshold, more diversity can be then detrimental to gain the returns of innovation. These arguments suggest that patent portfolio diversity is positively related to firm profitability but only up to a point. Beyond an ‘ideal’ level of diversity and inflection point maybe be reached after which costs become greater than the benefits of diversity which leads to a profitability decrease. This reasoning leads us to the following hypothesis:

Hypothesis 1: The relationship between patent portfolio diversity and firm profitability is curvilinear (inverted U-shaped) with the highest profitability occurring at an intermediate level of diversity.

3.2 The moderating role of non-self forward citations

Citations received by a patent reflect the intellectual lineage of the patent and the impact that the patent has on subsequent technological developments (Ketchen et al., 2013). Thus, the foeard citations (FCs) that a firm’s patents receive from subsequent patents have been acknowledged as a valid measure of technological importance (Hall et al., 2005; Ketchen et al., 2013; Trajtenberg, 1990). Furthermore, FCs are useful to evaluate the quality of a patent portfolio and they have a positive impact on market value (Chen & Chang, 2009; Lin et al., 2006). In addition, there is a positive relationship between FCs and payment of renewal fees. These maintenance fees, due every four years, are typically high and allow the patent owner to retain the patent’s protection. For this reason, renewal fees are paid only if the patent is valuable to the firm. The more the patent is cited, the higher are the probability of renewal. Consequently, the more the patent is cited, the higher the importance to the firm (Hedge & Sampat, 2009). FCs are generated after several years and when innovation uncertainty is notably decreased. Each new citation has a great positive effect on market value (Hall et al., 2005; Bessen, 2009). However, to avoid potential measurement noise, we considered the distinction between self and non-self FCs (Grimaldi et al., 2014; Hall et al., 2001).

Non-self FCs reveal a stream of knowledge between the firm and the marketplace. They constitute a "paper trail", highlighting connections among patents owned by different firms. Non-self FCs are important to understand the technology position of a patent portfolio in the market. The higher the number of non-self FCs, the more a firm's technology is 'picked-up' by competitors and other firms in the invention landscape. Potentially, this may result in profitability decay. The reason why this can arise is because of the lowering of technological asymmetries—the more one firm exposes its technology, the higher the probability that others are able to observe this technology and associated practices and thereby lower the chances to profit from that invention for a longer period of time. Confronted with the paradox of disclosing novelty through patenting, firms may not be able to sustain their profitability levels over long periods of time. It is not by chance that the number of citations is higher for breakthrough innovations of general purpose technologies (Youtie et al., 2008), which with their novelty heavily influence the field (Kaplan & Vakili, 2014). Non-self FCs are also an indicator of knowledge spillover, which is the uncompensated benefit that a firm's activity provides to another external firm; under this respect, non-self FCs work to the competitors' advantage. Knowledge spillovers are largely beyond the control of originating firms. Although non-self FCs potentially allow firms to better exploit their patent portfolio diversity, they do not always allow them to reach successively greater levels profitability. Overall, under circumstances of high spillovers, the better option for firms would be to reach moderate levels of patent portfolio diversity (i.e. diversity values higher than the mean value). This leads us to the following hypothesis:

Hypothesis 2: Non-self forward citations positively moderate the inverted U-shape relationship between patent portfolio diversity and firm profitability, such that increasing numbers of non-self forward citations reduce the negative concavity of the curve.

3.3 The moderating role of non-self backward citations

Backward citations (BCs) reveal the retrospective foundation on which an invention is realized. They signal the importance of external knowledge to the firm's ability to develop new technologies. That is, the higher the number of citations made, the more the firm appropriates advantage from technologies owned by others. References to knowledge in previous patents provide information on the nature and originality of the research contributing to a patent (Jaffe et al., 2002; Trajtenberg et al., 1997). BCs are also positively related to the value of a patent (Harhoff et al., 2003; Gambardella et al., 2005; Arts et al., 2013). Indeed, Schoenmakers & Duysters (2010) demonstrate how BCs can contribute to the radicalness of technological inventions. More creative inventions have been identified as displaying novel pairwise combinations of technology subclasses or components at the patent level (Fleming et al., 2007). In order to avoid measurement noise and ambiguity deriving from operationalizing BCs as a mere overall count (Thompson, 2016), we disentangle the number of non-self BCs as they reasonably account for the firm's absorptive capacity, classically defined as "the ability of a firm to recognize the value of new, external information, assimilate it, and apply it to commercial ends" (Cohen & Levinthal, 1990).

Absorptive capacity is composed of four distinct capabilities: acquisition, assimilation, transformation, and exploitation (Zahra & George, 2002). By considering these capabilities, absorptive capacity can be differentiated into two subsets: potential absorptive capacity and realized absorptive capacity. The former refers to the firm's ability of acquisition and assimilation and is the ability to recognize external knowledge, interpret and understand it. Instead, realized absorptive capacity is related to transformation and exploitation and is the firm's ability to use external knowledge in order to incorporate it into its technology or develop new ideas. Therefore, non-self BCs point to a firm's potential and realized absorptive capacity, which enhances innovative capacity and firm's value. This helps companies' units to develop the ability to generate breakthrough inventions (Ahuja & Lampert, 2001). According to Jansen et al. (2005, p. 999) "firms focusing on transformation and exploitation (realized absorptive capacity) may achieve short-term profits through exploitation but fall into a competence trap and may not be able to respond to environmental changes."

Notwithstanding the value of relying on external knowledge sources, some scholars highlight that too much reliance on what others have created may push firms to indulge in local search behaviors (Nelson & Winter, 1982). Such states may force firms to recombine 'old' knowledge while overlooking breakthrough inventions. Also, the more firms rely on external knowledge, the lower their potential to jump from one technological trajectory another. Finally, overcoming a certain threshold of non-self BCs, firms may encounter the 'over-search problem' (Martini et al., 2017), whereby the routines of internal integration mechanisms and idea management systems may, in turn, generate high rates of false-positives. Given that this is the case for a limited set of patents, it is even more vital when considering strategic choices pertaining to entire patent portfolios. Consequently, we may speculate that the number of non-self BCs moderates the relationship between diversity and the firm's profitability. In particular, high non-self BCs show that firms are able to recognize and exploit new opportunities and different technologies, but overcoming a certain threshold implies experiencing the over-search problem. This leads us to the following hypothesis:

Hypothesis 3: Non-self BCs negatively moderate the inverted U-shape relationship between diversity and profitability, such that increasing numbers of non-self BCs accentuate the negative concavity of the curve.

Figure 1 represents our conceptual model and hypotheses.

[Figure 1 here]

4. RESEARCH DESIGN

4.1 Data Collection and Method

This study analyzes international firms from three of the most patent-intensive subsectors[1] of manufacturing. These were identified in the North American Industry Classification System (NAICS): machinery manufacturing (NAICS333); computer and electronic product manufacturing (NAICS334); electrical equipment, appliance, and component manufacturing (NAICS335). We collected lagged financial performance data across the temporal horizon of 2010-2014. The source of these data was Osiris with patent portfolio data being drawn from the patent database PatBase. We restricted our analysis only to firms satisfying the following two criteria: 1) ≥250 employees[2] (average number over the last two years); and, 2) data regarding R&D expenditures in the last five years being available. In addition, we considered only portfolios including: patents granted by USPTO; patents with the earliest publication date between 2000 and 2010; patent portfolio size > 8 (i.e. we exclude firms which have a number of patents smaller than the number of IPC technological sections). Overall, our dataset includes 391 international firms with patents granted in the US, firms meeting our criteria are classified in the industry NAICS334 (for the 77.75%), NAICS333 (for 16.41%) and in NAICS335 (5.84%). To test each hypothesis, the software package SPSS (v.24) was used. We mean-centered both independent and moderating variables and used the hierarchical regression method for the performance variable. In order to ensure the correct interpretation of the results, we excluded outliers for the dependent variables from the sample (± 3 Std. Dev.).

4.2 Independent and Moderating Variables

[1] Patents by NAICS: http://www.uspto.gov/web/offices/ac/ido/oeip/taf/naics/naics_toc.htm Using patents by NAICS is an approximation allowing us to associate patents with sectors. A limitation may be that not all the products of the 391 selected companies fall under the most patent-intensive categories.

[2] Small firms are not considered in the calculation for entropy-based indicators because a critical mass of patents is needed.

This study measures patent portfolio diversity with an entropy-based measure (Palepu,1985) dealing with the three levels of the IPC classification: sections, classes, sub-classes. The motivation to use entropy-based indicators traces back to the 1960s. At that time, in the wake of information theorists' studies (Pielou, 1975), measuring diversity could be carried out by measuring the information content of a long string of symbols (Shannon and Weaver, 1949). The notion underlying this analogy views an ecological sample of species as a 'message' with individual organisms as pieces of 'information' (Maurer and McGill, 2011). Since then, entropy-based indicators have been widely used in a number of different areas such as ecology, geography, urban planning, psychology, linguistics, sociology, economics, and communication (McDonald and Dimmick, 2003). Innovation research is no exception and entropy-based indicators have been used to assess various phenomena including the potential of technological innovations (Zhang et al., 2017), technological emergence (Avila-Robinson and Miyazaki, 2013), domain interdisciplinarity (Porter and Rafols, 2009), and knowledge recombination (Appio et al., 2017). According to Junge (1994), these indicators are useful in assessing dual-concept diversity: "in statistical terms, a measure (index) of diversity is a summary description of a population with a class structure. More generally, quantification of diversity is related to the apportionment of some quantity (e.g., number of elements, time, mass) into a number of well-defined classes … the complete or dual-concept type of diversity index reflects both the number of classes and the degree of evenness of the apportionment" (Junge, 1994, p. 16).

In our study, the ecological species refer to IPC sections, classes, and subclasses; whilst, the number of individual organisms would indicate their relative abundance. A general measure of information content for an infinitely large set of symbols is called Renyi entropy of order α. The value of interest for this study is the limit of the equation (Hill, 1973; Pielou, 1975) when α approaches 1, which yields:

$$H = -\sum_{i=1}^{N} p_i \ln(p_i)$$

where p_i is the proportion of elements belonging to the ith group. This is the Shannon-Wiener measure of species diversity: the more the elements are equally distributed among the groups, the higher the value of the H index. Based on the IPC classification[3], we calculated three H indices: H_1 refers to 8 sections; H_2 refers to 127 classes; H_3 refers to 367 sub-classes. All diversity indices have been jack-knifed (bias-reduction method). The jack-knife is a general statistical technique for reducing the bias of an estimator by removing subsets of the data and recalculating the estimator with the reduced sample (Magurran and McGill, 2011).

To test our second and third hypotheses, as our level of analysis is the firm, we aggregate the total number of non-self FCs and non-self BCs for the entire portfolio and normalize them by portfolio size:

$$FCs = \frac{Number\ of\ non{-}self\ FCs}{Number\ of\ patents\ in\ the\ portfolio},\ BCs = \frac{Number\ of\ non{-}self\ BCs}{Number\ of\ patents\ in\ the\ portfolio}$$

4.3 Control Variables

We constructed two dummy variables to control for systematic industry effects, using NAICS334 (computer and electronic product manufacturing) as the baseline. We also considered the patent breadth as the total number of technological groups where patents were filed (Fernhaber and Patel, 2012). This index was calculated as the number of sections, classes and sub-classes the firms hold patents in. Other control variables are multiplicity (measured as the natural logarithm of the portfolio size), firm's size (measured as the natural logarithm of the average operating revenues,

[3] http://www.wipo.int/classifications/ipc/en/

or the average sale associated to the firm's core operations considering the years from 2010 to 2014), and R&D expenditures (measured as the ratio between R&D expenditures and operating revenues in the years from 2010 to 2014).

4.4 Dependent Variables

Consistent with other studies (Barnett et al., 1994; Zajac et al., 2000; Sørensen, 2002; Bae and Gargiulo, 2004. Lin et al., 2006), we chose Return on Assets (ROA) as the profitability index. While discussion concerning the most appropriate indicators of firm profitability is widespread (e.g., Scherer and Ross, 1990; Venkatraman and Ramanujam, 1986), ROA remains a widely adopted measure in innovation studies (Artz et al., 2010; Roberts and Amit, 2003; Sher and Yang, 2005) as it evaluates the ability of a firm to generate earnings from its asset or investment base.

As robustness check, we also considered Profit Margin (profit as a percentage of revenues), Return on Equity (ROE), and Cash Flows. Table 1 provides a summary of the used variables.

[Table 1 here]

5. RESULTS

Table 2 presents the correlation coefficients among the key variables, along with their means and standard deviations.

[Table 2 here]

It is worth noting that ROA shows a positive and significant ($p \leq 0.01$) correlation with both the diversity and breadth levels, signaling (especially at Section level) that potentially the higher the number of technological sections considered in the patent portfolio, the higher the ROA. On the contrary, a negative and significant ($p \leq 0.05$) correlation emerges between ROA and the adjusted measure of non-self FCs. We may preliminarily conclude that the higher the technological acceptance from external organizations, the lower the chances to gain higher levels of ROA. This may be consistent with the existence of a threshold beyond which negative returns show up. A similar conclusion may hold for the adjusted measure of non-self BCs, but in this case, the correlation is not significant. Results concerning the testing of the three hypotheses follow.

5.1 Testing Hypothesis 1

Hypothesis 1 suggests an inverted-U shape relationship between patent portfolio diversity and firm profitability. Formally[4]:

$$Performance = \beta_0 + \beta_1 {H'}_k^{2} + \beta_2 {H'}_k + \sum_{i=3}^{10} \beta_i Controls_i \tag{1}$$

where k (from 1 to 3) identifies the considered level of the IPC classification. We then tested our hypotheses (Table 3).

[Table 3 here]

When considering the patent portfolio diversity at the Section level (Figure 2), results support our hypothesis (β_1= -7.44, p $\leq$ 0.01). Considering the patent portfolio diversity both at the classes and sub-classes levels, hypothesis 1 is not supported.

[Figure 2 here]

5.2 Testing Hypothesis 2

Hypothesis 2 asserts that the number of non-self FCs moderates the inverted-U shape relationship between diversity and profitability (Table 4). Formally[5]:

$$Performance = \beta_0 + (\beta_1 FCs + \beta_3){H'}_k^{2} + (\beta_2 FCs + \beta_5){H'}_k + \beta_4 FCs^2 + \beta_6 FCs + \sum_{i=7}^{14} \beta_i Controls_i \tag{2}$$

[4] Control variables: Dummy NAICS333, Dummy NAICS335, Multiplicity, Firm’s size, R&D expenditures, Breadth sections, Breadth classes, Breadth sub-classes.

[5] Control variables considered: Dummy NAICS333, Dummy NAICS335, Multiplicity, Firm’s size, R&D expenditures, Breadth sections, Breadth classes, Breadth sub-classes.

where *k* (from 1 to 3) identifies the considered level of the IPC classification. We hypothesized that high numbers of FCs reduce the negative concavity of the relationship between patent portfolio diversity and profitability. We employed three models for each profitability variable: a model that considers only control variables and direct effects, a model with the addition of the linear moderating effects, and another with the addition of the non-linear moderating effects.

[Table 4 here]

Considering H_1, results do not support this hypothesis (β_1=-1.78; $p \leq 0.01$). However, results highlight a significant positive coefficient for the linear interaction of patent portfolio diversity and FCs. This holds for the second model (which excludes non-linear moderating effects) as well. Finally, considering the sub-class level (H_3), results do not confirm expectations (β_1=-0.26; $p<0.1$). Just as for H_2, the second model shows a significant positive effect of the linear interaction of patent portfolio diversity and FCs for ROA. Figure 3 reveals the relationship between H_1 and profitability for high, average, and low number of FCs. For low levels of FCs, the coefficient of H_2 becomes positive and modifies the concavity of the curve. For high levels of FCs, the relationship between profitability and patent portfolio diversity has a more accentuated negative concavity. As shown in Figure 3, in correspondence of low degrees of diversity firms reach greater profitability for low numbers for FCs, even though the curve has a negative slope. Beyond the crossing point of the curves, high numbers of FCs correspond to higher levels of profitability.

[Figure 3 here]

5.3 Testing Hypothesis 3

Hypothesis 3 advances that the number of non-self backward citations moderates the inverted-U shape relationship between diversity and profitability (Table 5). Formally[6]:

$$Performance = \beta_0 + (\beta_1 BCs + \beta_3){H'_k}^2 + (\beta_2 BCs + \beta_5)H'_k + \beta_4 BCs^2 + \beta_5 BCs + \sum_{i=6}^{13} \beta_i Controls_i \quad (3)$$

where *k* (from 1 to 3) identifies the considered level of the IPC classification. We hypothesized that high numbers of non-self BCs accentuate the negative concavity of the relationship between patent portfolio diversity and profitability.

[Table 5 here]

Considering diversity at the level of sections, results support the expectation (β_1=-0.82; $p \leq 0.05$). In addition, we found significant positive effects of the linear interaction of patent portfolio diversity and BCs for the profitability measure. Considering diversity at the class level, we found support for our hypothesis (β_1= -0.35; $p \leq 0.05$). Again, we found significant positive effects of the linear interaction of patent portfolio diversity and BCs for the profitability measure. Finally, considering diversity at sub-classes level, results confirm the hypothesis (β_1= -0.28; $p \leq 0.01$) and a significant positive effect of the linear interaction of patent portfolio diversity and BCs for the profitability measure.

Figure 4 shows the relationship between patent portfolio diversity considering sections (H_1) and profitability, for high, average, and low number of BCs. For high levels of BCs, such relationship has a more accentuated concavity and maximum point of the curve is higher. Moreover, because of the positive linear interaction between patent portfolio diversity and profitability, the maximum is reached in correspondence of higher degrees of patent portfolio diversity, thus firms can benefit from growing profitability in correspondence to larger ranges of

[6] Control variables considered: Dummy NAICS333, Dummy NAICS335, Multiplicity, Firm's size, R&D expenditures, Breadth sections, Breadth classes, Breadth sub-classes.

patent portfolio diversity. For low levels of BCs, the coefficient of H_1^2 becomes closer to zero, thus the relationship between H_1 and profitability becomes almost linear negative.

[Figure 4 here]

Overall, results support several but not all of our hypotheses. Results fundamentally vary depending on the level at which we considered patent portfolio diversity. Indeed, results are more significant considering patent portfolio diversity at the section level. By considering diversity both at class and sub-class levels, results are less significant and sometimes contradict the expected relationships. By performing a robustness check on other profitability measures (ROE, Profit Margin, Cash Flow)[7], we observed that the results change depending on the measure considered. Table 6 offers a synopsis of our data analysis scheme and reports the hypotheses and associated key findings.

[Table 6 here]

6. CONCLUSIONS AND IMPLICATIONS

We contribute with a systematic analysis of the relationship between patent portfolio diversity and firm profitability. Our findings highlight how the non-linear relationship between patent portfolio diversity and profitability varies depending on the level of non-self FCs and BCs. In doing so, we relied on a sample of 391 international firms and considered patent portfolio diversity at the level of sections, classes, and sub-classes (following the structure of the IPC classification). Each model was then tested in relation to ROA, and a robustness check has been performed on profit margin, ROE and cash flow as well. We revealed that findings vary according to the level of the technological classification considered. This is supposedly due to the hierarchical structure of the

[7] Correlation between ROA and: Profit Margin (0.909, $p<0.01$), ROE (0.801, $p<0.01$), Cash Flow (0.471, $p<0.01$).

IPC classification. As a consequence, the measure of diversity at one level does not take into account diversification at underlying levels. Also, our findings support the existence of an inverted-U relationship between patent portfolio diversity at the section level and ROA. Therefore, results strengthen the idea that profitability increases until a certain level of patent portfolio diversity, reaches a maximum and then decreases.

Considering the nature of data, we observe that profitability reaches the maximum impact on profitability for low levels of diversity and then decreases. This suggests that very low or very high patent portfolio diversity are likely to result in lower profitability than average levels of diversity. We tested the relationship between patent portfolio diversity and profitability by accounting for the influence of two specific moderators: non-self FCs, which are a proxy of the quality of firm's technology and its spillover in the market; non-self BCs, which are a proxy of absorptive capacity. Results indicate that, contrary to our expectations, FCs accentuate the negative concavity of patent portfolio diversity–profitability relationship. Although they potentially allow firms to better exploit patent portfolio diversity, they not always allow them to reach greater profitability. This suggests that in presence of high spillovers, the better option for firms is to reach moderate levels of patent portfolio diversity (i.e. diversity values higher than the mean value). On the contrary, for portfolios with patents that are not especially significant for the market or not of high quality, high profitability is generated from low levels of diversity.

Concerning the second moderator, results show that high numbers of non-self BCs accentuate the concavity of the relationship between patent portfolio diversity and profitability. This finding is stable considering diversity at all levels and supports the thesis that high absorptive capacity allows firms to better recognize external opportunities, also coming from different technological firms. Absorptive capacity, therefore, enhances firms' ability to manage technologies across different fields and, in correspondence of high levels of diversity, allows to reach higher profitability. Indeed, for low levels of non-self BCs, profitability decreases as patent portfolio diversity increases. This supports the thesis that for low absorptive capacity firms do not have the ability to successfully use knowledge from different technological fields. In such situations, a better strategy may be that of focusing on a limited number of technological fields.

By performing a robustness check, results seem to vary depending on the profitability measure considered, sometimes showing unexpected results. Specifically, considering the diversity at the level of sub-classes and ROE, results refuted the hypothesis of an inverted U-shape relationship between patent portfolio diversity and profitability. Thus, in this case, we found a U-shaped relationship, signaling that it may be better to avoid intermediate values of diversity. Finally, no significant variation is shown when it comes to multiplicity (no significant effects) and firm size (always positive and significant effects). The latter shows that the larger the firms (in terms of average operating revenues), the larger the effect on the ROA and this holds regardless the presence of both non-self BCs and FCs as moderators. Also, larger firms tend to have higher performance, regardless of the level of technological diversity we consider.

There are several implications of our research. The results clearly show differences in the behavior of the profitability curve whenever patent portfolio diversity is considered at the level of section, classes or sub-classes. This is potentially due to the structure of the IPC classification. Indeed, this classification follows a hierarchical method: the 8 sections are in turn divided into one 127 classes, which in turn are divided into 367 subclasses. This may explain why results differ across the considered levels of diversity. If we suppose, for instance, all patents of a specific firm are classified in one technological section only, we may have a minimum level of diversity at this level. However, the section is divided into several technological classes, and patents could spread across these levels. Therefore, the measure of diversity at one level does not seem to take into account the measure of diversity at more underlying levels. At the level of sections, our findings support the presence of a non-linear diversity-profitability relationship that is subject to the influence of the moderators. This means that keeping constant the degree of patent portfolio diversity, different firms do not reach the same profitability, calling then for considering different strategies. It is particularly important to take into account the absorptive capacity of firms and its ability to learn vicariously for the external environment. With these greater abilities, the higher is the firm's chance to perform successful diversification. Practically, this means that firms that intend to diversify their range of technologies need to accurately select their patent portfolio's composition and nurture their capacity to take advantage from diversification. The talent to steer the activity to promising technological fields depends on the capability to absorb external knowledge and maintain a competitive advantage in the market. Both external non-self FCs and BCs are measures of these abilities, and both partly depend on external sourcing technology, which requires various levels of flexibility and commitment. In short, the firm's willingness to pursue a technology diversification strategy should be sustained by alliances or external collaborations that allow for knowledge sharing.

7. LIMITATIONS AND FUTURE RESEARCH

Our work is subject to a number of limitations that should be taken into account while interpreting the results. Our sampling frame is limited to patents filed with the USPTO between 2000 and 2010, and to three focal sectors (i.e. NAICS 333,334,335). Due the characteristics of the sectors included in our study, our findings may apply to industries where patenting cycles are relatively short and dynamic, and R&D and patenting activities are not heavily regulated. In contrast, our results may not generalize to industries with longer R&D and patenting cycles, and/or where these activities are highly regulated. Key examples of the latter are healthcare and pharma sectors, where the nature of the relationship between patent portfolio diversity and profitability may be subject to different rules. Future research may look into replicating and extending our findings in light of key differences across these salient dimensions. Some further avenues for future research emerge from this study. We demonstrated the lack of universal generalizations and importance of considering complexity as a result of the interaction of different aspects of patent portfolios. Established empirical precedent developed the topic of complexity in various ways but most particularly by the analysis of product portfolios or alliances portfolios. However, certain conflation emerges concerning the definition of the complexity of patent portfolios especially when it comes to consider its measures and components. Future research, by entailing results concerning the interaction among different components, might provide a more rigorous characterization of the patent portfolio complexity.

A second fascinating question arises from the observation of differences in results on various profitability measures. We considered firms' profitability as our performance measures and, therefore, it can be interesting to take directly into account how patents contribute to the creation of profit. In detail, firms can exploit patented technology into two ways: by focusing the technology on their own products or by licensing activity. Previous literature (e.g., Blind et al., 2009; Somaya, 2012) focused on the relationship between portfolio characteristics and strategic drivers. Future research can move from this insight and focus on how patent strategy affects the relationship between patent portfolio complexity and firms' profitability.

Third, results highlight notable differences among diversity considered at the level of sections, classes, and sub-classes. We demonstrate that the relationship between patent portfolio diversity at the level of sections and profitability is influenced by the spread of patent at the underlying levels. Future research might investigate more closely if the ideal degree of diversity depends on the distribution of patents across technological classes or sub-classes. A study of this nature might actively contribute to defining a better strategy of patent portfolio management.

Fourth, the relationship between portfolio characteristics and firm profitability is complex and requires further investigation. Indeed, depending on the choice of measurement of portfolio's characteristics and the firm's profitability, the relationship may vary. For instance, it is possible to consider economic-financial performance in terms of profits, sales, market value, and similar measures, or innovative performance in terms of firm's capacity to create something different. The relationship between portfolio characteristics and firm's profitability may depend on several factors. Considering industry exigencies, sectors with different characteristics (e.g., healthcare, construction, ICT, and telecommunications) may require diverse approaches each generating different results (Chen and Chang, 2010). Also a differentiation between patent-intensive and nonpatent-intensive industries can be worthy of further investigation in order to understand whether—and to what extent—non-self BCs and FCs shape the link between patent portfolio diversity and firm profitability. Industrial affiliation and competitors' behaviors influence a firm's strategy and goals, and these can be classified in different ways (Blind et al., 2009; Somaya, 2012). Following Somaya (2012), it may be possible to identify three main general strategies. The first is the *proprietary strategy*, in which a patent portfolio is built with the aim to build barriers and block the entrance of competitors in the firm's market. The second is *defensive strategy*, which is followed with the purpose to guard against infringements of competitors' patents. The third is the *leverage strategy* with which the firm seeks to exploit the patent's bargain advantage. The same degree of patent portfolio complexity may correspond to different profitability implications depending on firm strategy (Blind et al., 2009). Finally, results could vary further subject to differing degrees of a firm's competitive position (Chen and Chang, 2010), internationalization (Cantwell and Piscitello, 2000), or experience (Heeley and Jacobson, 2008).

Acknowledgements

The authors kindly acknowledge the research assistance provided by Daniela Tuveri and Caroline Bird in undertaking this study.

REFERENCES

Ahuja, G., & Lampert, C.M. (2001). Entrepreneurship in the large corporation: A longitudinal study of how established firms create breakthrough inventions. *Strategic Management Journal, 22*, 521-543.

Aiken, L.S., & West, S.G. (1991). *Multiple regression: Testing and interpreting interactions*. Thousand Oaks, CA: Sage.

Ambrammal, S.K., & Sharma, R. (2016). Impact of patenting on firms' performance: An empirical investigation based on manufacturing firms in India. *Economics of Innovation and New Technology*, 25, 14-32.

Appio, F.P., Martini, A., & Fantoni, G. (2017). The light and shade of knowledge recombination: Insights from a general-purpose technology. *Technological Forecasting and Social Change, 125*, 154-165.

Arts, S., Appio, F.P., & Van Looy, B. (2013). Inventions shaping technological trajectories: Do existing patent indicators provide a comprehensive picture? *Scientometrics, 97*, 397-419.

Artz, K.W., Norman, P.M., Hatfield, D.E., & Cardinal, L.B. (2010). A Longitudinal Study of the Impact of R&D, Patents, and Product Innovation on Firm Performance. *Journal of Product Innovation Management, 27*, 725-740.

Avila-Robinson, A., & Miyazaki, K. (2013). Dynamics of scientific knowledge bases as proxies for discerning technological emergence- The case of MEMS/NEMS technologies. *Technological Forecasting and Social Change, 80*, 1071–1084.

Bae, J., & Gargiulo, M. (2004). Partner substitutability, alliance network structure, and firm profitability in the telecommunications industry. *Academy of Management Journal, 47*, 843-859.

Barnett, W.P., Greve, H.R., & Park, D.Y. (1994). An evolutionary model of organizational performance. *Strategic Management Journal, 15*, 11–28.

Bessen, J. (2009). Estimates of firms' patent rents from firm market value. *Research Policy, 38*, 1604-1616.

Blind, K., Cremers, K., & Mueller, E. (2009). The influence of strategic patenting on companies' patent portfolios. *Research Policy, 38*, 428-436.

Breschi, S., Lissoni, F., & Malerba, F. (2003). Knowledge relatedness in firms' technological diversification. *Research Policy, 32*, 69-87.

Callen, J.L., Gavious, I., & Segal, D. (2010). The complementary relationship between financial and non-financial information in the biotechnology industry and the degree of investor sophistication. *Journal of Contemporary Accounting & Economics, 6*, 61-76.

Caner, T., Bruyaka, O., & Prescott, J.E. (2017). Flow signals: Evidence from patent and alliance portfolios in the US biopharmaceutical industry. *Journal of Management Studies*, in Press.

Cantwell, J.A., & Piscitello, L. (2000). Accumulating technological competence: Its changing impact on corporate diversification and internalization. *Industrial and Corporate Change, 9*, 21-51.

Chen, Y.-S., & Chang, K.-C. (2010). The relationship between a firm's patent quality and its market value: The case of US pharmaceutical industry. *Technological Forecasting and Social Change, 77*, 20-33.

Chen, Y.-M., Yang, D.-H., & Lin, F.-J. (2013). Does technological diversification matter to firm performance? The moderating role of organizational slack. *Journal of Business Research, 66*, 1970-1975.

Cohen, W.M., & Levinthal, D.A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly, 35*, 128-152.

Cohen, W., Nelson, R., & Walsh, J. (2000). Protecting their intellectual assets: Appropriability conditions and why US manufacturing firms patent (or not). *NBER Working Paper*, No.7552.

Czarnitzki, D., & Kraft, K. (2010). On the profitability of innovative assets. *Applied Economics*, *42*, 1941-1953.

De Rassenfosse, G., & van Pottelsberghe de la Potterie, B. 2013. The role of fees in patent systems: theory and evidence. *Journal of Economic Surveys, 27*, 696-716.

Ernst, H. (2003). Patent information for strategic technology management. *World Patent Information, 25*, 233-242.

Ernst, H., Conley, J., & Olmland, N. (2016). How to create commercial value from patents: The role of patent management. *R&D Management, 46*, 677–690.

Fernhaber, S., & Patel, P. (2012). How do young firms manage product portfolio complexity? The role of absorptive capacity and ambidexterity. *Strategic Management Journal, 33*, 1516-1539.

Fleming, L., Mingo, S., & Chen, D. (2007). Collaborative brokerage, generative creativity and creative success. *Administrative Science Quarterly, 52*, 443–475.

Gambardella, A., Harhoff, D., & Verspagen, B. (2005). The value of European patents. *European Management Reviews, 5*, 69-84.

Garcìa-Vega, M. (2006). Does technological diversification promote innovation? An empirical analysis for European firms. *Research Policy, 35*, 230-246.

Graphar, F., Brooks, R., & Smyth, R. (2014). The impact of patenting activity on the financial performance of Malaysian firms. *Journal of the Asia Pacific Economy, 19*, 445-463.

Grimaldi, M., Cricelli, L., Di Giovanni, M., & Rogo, F. (2015). The patent portfolio value analysis: A new framework to leverage patent information for strategic technology planning. *Technological Forecasting and Social Change, 94*, 286-302.

Grupp, H. (1990). The concept of entropy in scientometrics and innovation research. *Scientometrics, 18*, 219–239.

Hall, B.H., Jaffe, A., & Trajtenberg, M. (2005). Market Value and Patent Citations. *The RAND Journal of Economics, 36*, 16-38.

Harhoff, D., Scherer, F.M., & Vopel, K. (2003). Citations, family size, opposition and the value of patent rights. *Research Policy, 32*, 1343-1363.

Harhoff, D., Hoisl, K., Reichl, B., &van Pottelsberghe de la Potterie, B. (2009). Patent validation at the country level – The role of fees and translation costs. *Research Policy, 38*, 1423-1437.

Heeley, M., & Jacobson, R. (2008). The recency of technological inputs and financial performance. *Strategic Management Journal, 29*, 723-744.

Hill, M.O. (1973). Diversity and evenness: A unifying notation and its consequences. *Ecology, 54*, 427-432.

Hirshleifer, D., Hsu, P.-H., & Li, D. (2017). Innovative originality, profitability, and stock returns. *Review of Financial Studies*, in Press.

Hirshleifer, D., Hsu, P.-H., & Li, D. (2013). Innovative efficiency and stock returns. *Journal of Financial Economics, 107*, 632-654.

Jacobs, M.A., & Swink, M. (2011). Product portfolio architectural complexity and operational performance: Incorporating the roles of learning and fixed assets. *Journal of Operations Management, 29*, 677-691.

Jaffe, A.B., M. Trajtenberg, & Fogarty, M. (2002). The meaning of patent citations: Report of the NBER/Case-Western Reserve survey of patentees. In A. Jaffe and M. Trajtenberg (Eds.), *Patents, citations, and innovations: A window on the knowledge economy* (pp. 379–402). Cambridge, MA: MIT Press.

Jansen, J.J.P., Van den Bosch, F.A.J., & Volberda, H.W. (2005). Managing potential and realized absorptive capacity: How do organizational antecedents matter? *Academy of Management Journal, 48*, 999-1015.

Jell, F., Henkel, J., & Wallin, M.W. (2017). Offensive patent portfolio races. *Long Range Planning, 50*, 531-549.

Junge, K. 1994. Diversity of ideas about diversity measurement. *Scandinavian Journal of Psychology*, 36, 16-26.

Kaplan, S., & Vakili, K. (2014). The double-edged sword of recombination in breakthrough innovation. *Strategic Management Journal, 36*, 1435-1457.

Ketchen, D.J., Ireland, R.D., & Baker, L.T., (2013). The use of archival proxies in strategic management studies: Castles made of sand? *Organizational Research Methods, 16*, 32-42.

Lai, Y.-L., Lin, F.-J., & Lin, Y.-H. (2015). Factors affecting firm's R&D investment decisions. *Journal of Business Research, 68*, 840-844.

Lawryshyn, Y., Collan, M., Luukka, P., & Fedrizzi, M. (2017). New procedure for valuing patents under imprecise information with a consensual dynamics model and a real options framework. *Expert Systems with Applications, 86*, 155-164.

Leten, B., Belderbos, R., & Van Looy, B. (2007). Technological diversification, coherence, and performance of firms. *Journal of Product Innovation Management, 24*, 567-579.

Lin, B.-W., Chen, C.-J., & Wu, H.-L. (2006). Patent portfolio diversity, technology strategy, and firm value. *IEEE Transactions on Engineering Management, 53*, 17-26.

Littmann-Hilmer, G., & Kickartz, M. (2009). SME tailor-designed patent portfolio analysis. *World Patent Information, 31*, 273-277.

Martini, A., Neirotti, P., & Appio, F.P. (2017). Knowledge searching, integrating and performing: Always a tuned trio for innovation? *Long Range Planning, 50*, 200-220.

McDonald, D.G., & Dimmick, J. (2003). The conceptualization and measurement of diversity. *Communication Research, 30*, 60–79.

Meyer, J., & Subramanian, M. (2014). Appropriating innovation's technical value: Examining the influence of exploration. *Journal of Business Research, 67*, 2860-2866.

Miller, D.J. (2006). Technological diversity, related diversification, and firm performance. *Strategic Management Journal, 27*, 601-619.

Nelson, R.R., & Winter, S.G. (1982). *An Evolutionary Theory of Economic Change*. Boston, MA: Harvard University Press.

OECD (2015). *OECD Science, Technology and Industry Scoreboard 2015: Innovation for Growth and Society*. OECD Publishing, Paris.

Palepu, K. (1985). Diversification Strategy, Profit Performance and the Entropy Measure. *Strategic Management Journal, 6*, 239-255.

Parchomovsky, G., & Wagner, P. (2005). Patent portfolios. *University of Pennsylvania Law Review, 154*, 1-77.

Patel, D., & Ward, M.R. (2011). Using patent citation patterns to infer innovation market competition. *Research Policy, 40*, 886-894.

Pohlmann, T., Neuhäusler, P., & Blind, K. (2016). Standard essential patents to boost financial returns. *R&D Management*, *46*, 612-630.

Porter, A., & Rafols, I. (2009). Is science becoming more interdisciplinary? Measuring and mapping six research fields over time. *Scientometrics, 81*, 719–745.

Quintana-Garcìa, C., & Benavides-Velasco, C. (2007). Innovative competence, exploration and exploitation: The influence of technological diversification. *Research Policy, 37*, 492-507.

Roberts, P.W., & Amit, R. (2003). The Dynamics of Innovative Activity and Competitive Advantage: The Case of Australian Retail Banking, 1981–1995. *Organization Science, 14*, 107–122.

Sampson, R.C. (2007). R&D alliances and firm performance: The impact of technological diversity and alliance organization on innovation. *Academy of Management Journal, 50*, 364-386.

Samuelson, P., & Scotchmer, S. (2002). The law and economics of reverse engineering. *Yale Law Journal, 111*, 1575-1663.

Schoenmakers, W., & Duysters, G. (2010). The technological origins of radical inventions. *Research Policy, 39*, 1051-1059.

Shankerman, M. (1998). How valuable is patent protection? Estimates by technology field. *RAND Journal of Economics, 29*, 77-107.

Shannon, C., & Weaver, W. (1949). *The mathematical theory of communication*. Urbana: University of Illinois Press.

Sher, P.J., & Yang, P.Y. (2005). The Effects of Innovative Capabilities and R&D Clustering on Firm Performance: The Evidence of Taiwan's Semiconductor Industry. *Technovation, 25*, 33–43.

Scherer, F.M., & Ross, D. (1990). *Industrial Market Structure and Economic Performance*. Boston, MA: Houghton Mifflin.

Somaya, D. (2012). Patent strategy and management: An integrative review and research agenda. *Journal of Management, 38*, 1084-1114.

Sørensen, J.B. (2002). The strength of corporate culture and the reliability of firm performance. *Administrative Science Quarterly, 47*, 70–91.

Stirling, A. (2007). A general framework for analysing diversity in science, technology and society. *Journal of the Royal Society Interface, 4*, 707-719.

Thompson, M.J. (2016). Measuring patent quality: A claim and search report approach. *World Patent Information, 45*, 47-54.

Trajtenberg, M. (1990). A penny for your quotes: Patent citations and the value of innovations. *The RAND Journal of Economics, 21*, 172-187.

Trajtenberg, M., Henderson, R., & Jaffe, A.B. (1997). University versus corporate patents: A window on the basicness of invention. *Economics of Innovation and New Technology, 5*, 19–50.

Van-Triest, S., & Vis, W. (2007). Valuing Patents on Cost-reducing Technology: A Case Study. *International Journal of Production Economics*, 105, 282–292.

Venkatraman, N., & Ramanujam, V. (1986). Measurement of Business Performance in Strategy Research: A Comparison of Approaches. *Academy of Management Review, 11*, 801–814.

Wilhelmsson, L., & Mcqueen, D. (1999). Product diversity and performance: A macro study of 20 large Swedish industrial corporations. *Scandinavian Journal of Management, 15*, 43-64.

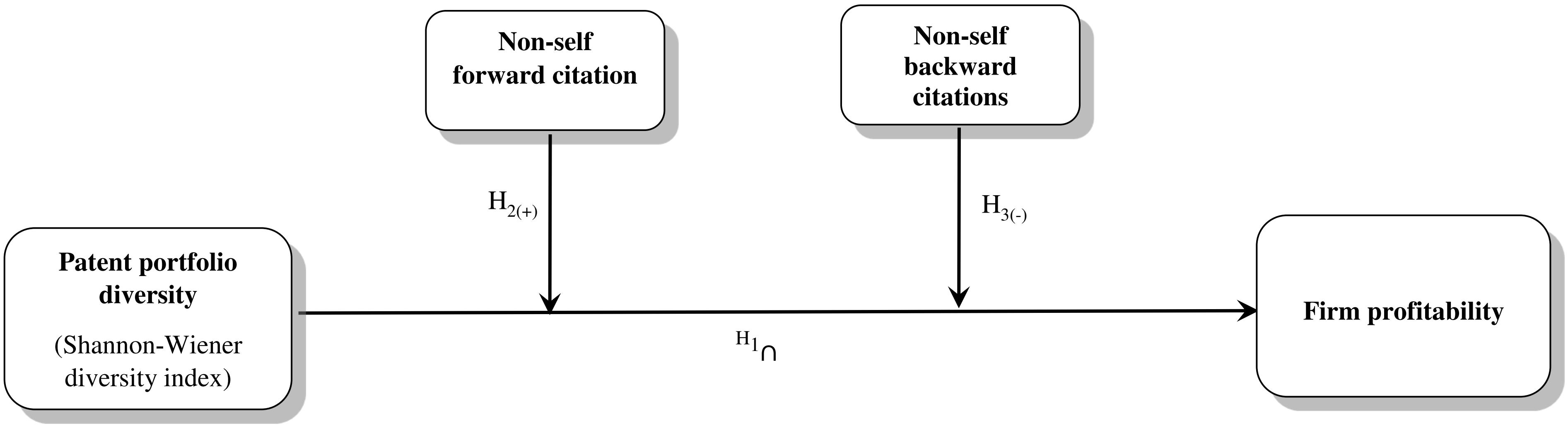
Yang, H., Phelps, C., & Steensma, H.K. (2010). Learning from what others have learned from you: The effects of knowledge spillovers on originating firms. *Academy of Management Journal*, *53*, 371-389.

Youtie, J., Iacopetta, M., & Graham, S. (2008). Assessing the nature of nanotechnology: Can we uncover an emerging general purpose technology? *Journal of Technology Transfer, 33*, 315-329.

Zahra, S.A., & George, G. (2002). Absorptive capacity: A review, reconceptualization, and extension. *Academy of Management Review, 27*, 185-203.

Zajac, E.J., Kraatz, M.S., & Bresser, R.K.F. (2000). Modeling the dynamics of strategic fit: A normative approach to strategic change. *Strategic Management Journal, 21*, 429–453.

Zhang, Y., Qian, Y., Huang, Y., Guo, Y., Zhang, G., & Lu, J. (2017). An entropy-based indicator system for measuring the potential of patents in technological innovation: Rejecting moderation. *Scientometrics, 111*, 1925-1946.



Patent classification levels
Section: (H'_1)
Section: (H'_2)
Section: (H'_3)

Profitability measure
Main analysis: return on assets
Robustness tests: profit margin, return on expenditure and cashflows

Figure 1. Conceptual model

Table 1. Variables and measures

Variable type	Variable name	Measure
Independent Variables	Diversity at Section level (k=1)	$\mathrm{H'1} = -\sum_{i=1}^{8} p_i \ln(p_i)$
	Diversity at Class level (k=2)	$\mathrm{H'2} = -\sum_{i=1}^{127} p_i \ln(p_i)$
	Diversity at Sub-class level (k=3)	$\mathrm{H'3} = -\sum_{i=1}^{367} p_i \ln(p_i)$
Moderating Variables	Adjusted Forward Citations	$= \frac{\text{Number of non} - \text{self FCs}}{\text{Number of patents in the portfolio}}$
	Adjusted Backward Citations	$= \frac{\text{Number of non} - \text{self BCs}}{\text{Number of patents in the portfolio}}$
Control Variables	Dummy NAICS333	1 if the firm belong to NAICS 333, 0 otherwise
	Dummy NAICS335	1 if the firm belong to NAICS 335, 0 otherwise
	Breadth at Section level	Breadth_1, number of technological section where patents were filed
	Breadth at Class level	Breadth_2, number of technological classes where patents were filed
	Breadth at Sub-class level	Breadth_3, number of technological Sub-classes where patents were filed
	Firm Size	ln ($\sum_{i=1}^{5}$ Operating Revenues/5)
	R&D Expenditures	($\sum_{i=1}^{5}$ R&D Expenditures/Operating Revenue)/5
	Multiplicity	ln (number of patents in the portfolio)
Dependent Variable	ROA	Average Return on Assets of the last five years

Table 2. Pearson's Correlation matrix

	H1	H2	H3	Dummy NAICS333	Dummy NAICS335	Breadth Sections	Breadth Classes	Breadth Sub-classes	Profit Margin	ROE	ROA	Cash Flow	Adj. FCs	Adj. BCs	Multiplicity	Size	R&D exp.
H1	1																
H2	.774**	1															
H3	.561**	.842**	1														
Dummy NAICS333	.317**	.339**	.249**	1													
Dummy NAICS335	.157**	.128*	.120*	-.111*	1												
Breadth Sections	.613**	.679**	.674**	.233**	0.090	1											
Breadth Classes	.459**	.642**	.702**	.224**	-0.010	.773**	1										
Breadth Sub-classes	.353**	.553**	.666**	.172**	-0.041	.693**	.975**	1									
Profit Margin	0.082	.123*	.150**	.139**	-0.029	.183**	.191**	.210**	1								
ROE	.116*	.115*	.127*	.175**	0.027	.115*	.118*	.117*	.700**	1							
ROA	.132**	.153**	.165**	.147**	-0.010	.187**	.160**	.168**	.909**	.801**	1						
Cash Flow	-0.024	-0.009	0.028	-0.041	-0.015	.105*	.186**	.205**	.604**	.303**	.471**	1					
Adj. FCs	-.104*	-.196**	-0.097	-.147**	0.020	-.129*	-.170**	-.174**	-.122*	-0.072	-.110*	0.003	1				
Adj. BCs	0.090	-0.053	0.019	0.040	.156**	-0.050	-.213**	-.258**	-0.084	-0.033	-0.072	-0.029	.730**	1			
Multiplicity	0.090	.346**	.480**	0.038	-.108*	.640**	.825**	.837**	.195**	0.090	.146**	.265**	-.141**	-.312**	1		
Size	.272**	.386**	.481**	.138**	0.036	.589**	.696**	.697**	.335**	.267**	.309**	.152**	-0.042	-0.095	.663**	1	
R&D exp.	-.364**	-.271**	-.124*	-.245**	-.137**	-.224**	-.136**	-0.086	-.316**	-.317**	-.365**	.123*	.160**	0.057	0.090	-.301**	1
Mean	.9626	1.882	2.675	.1601	.0604	5.346	24.06	56.46	3.534	2.476	2.946	11.87	9.529	13.33	4.588	6.604	10.82
Std. Dev.	.3405	.5690	.6993	.3672	.2385	1.720	19.24	58.91	14.99	28.78	11.03	7.542	9.111	7.850	1.544	1.609	10.05

****. Correlation is significant at the 0.01 level (2-tailed).**

***. Correlation is significant at the 0.05 level (2-tailed).**

Table 3. Testing Hypothesis 1

	1	2	3	1	2	3	1	2	3
Linear Effects									
H'$_1$		-2.33	-2.11						
		(1.76)	(1.75)						
H'$_2$					-0.67	-1.21			
					(1.04)	(1.10)			
H'$_3$								-0.26	0.38
								(0.80)	(0.89)
Non-Linear Effects									
H'$_1^2$			-7.44***						
			(2.82)						
H'$_2^2$						-1.54			
						(1.05)			
H'$_3^2$									1.05
									(0.66)
Controls									
Dummy NAICS333	2.66**	2.88**	3.46***	2.80**	2.94**	3.17***	2.44**	2.51**	2.33**
	(1.15)	(1.16)	(1.17)	(1.16)	(1.18)	(1.19)	(1.14)	(1.16)	(1.17)
Dummy NAICS335	0.23	0.32	0.8	0.07	0.24	0.26	-0.18	-0.07	-0.16
	(1.79)	(1.79)	(1.79)	(1.77)	(1.79)	(1.79)	(1.77)	(1.80)	(1.80)
Multiplicity	0.03	-0.23	-0.24	0.32	0.21	-0.1	-0.04	-0.06	0.2
	(0.45)	(0.49)	(0.49)	(0.54)	(0.57)	(0.61)	(0.54)	(0.54)	(0.56)
Firm size	1.49***	1.52***	1.63***	1.55***	1.53***	1.60***	1.49***	1.50***	1.47***
	(0.39)	(0.39)	(0.39)	(0.39)	(0.40)	(0.40)	(0.40)	(0.40)	(0.40)
R&D expenditures	-0.071	-0.077	-0.084	-0.07	-0.07	-0.07	-0.06	-0.06	-0.05
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Breadth sections	-0.48*	-0.08	-0.21	-0.07	-0.05	-0.01	-0.01	-0.01	-0.02
	(0.34)	(0.45)	(0.45)	(0.04)	(0.05)	(0.06)	(0.01)	(0.02)	(0.02)
Intercept	-3.87**	-5.04**	-4.31**	-6.535***	-6.44***	-5.82***	-5.54**	-5.63**	-6.38***
	(2.66)	(2.01)	(2.02)	(2.80)	(2.18)	(2.22)	(2.44)	(2.36)	(2.40)
F-stat	7.05***	6.30***	6.47***	7.150***	6.18***	5.69***	6.77***	5.80***	5.41***
R^2	0.10	0.11	0.12	0.104	0.10	0.11	0.10	0.10	0.11
ΔF-stat	7.05***	1.76	6.96***	7.150***	0.42	2.14	6.77	0.10	2.54
Adjusted-R^2	0.09	0.09	0.1	0.09	0.09	0.09	0.08	0.08	0.09
Sample size	376	376	376	376	376	376	376	376	376
Highest VIF	3.14	3.83	3.87	4.57	6.34	7.57	4.12	5.14	6.65

*$p \leq 0.1$ **$p \leq 0.05$ ***$p \leq 0.01$*
All diversity indicators jack-knifed

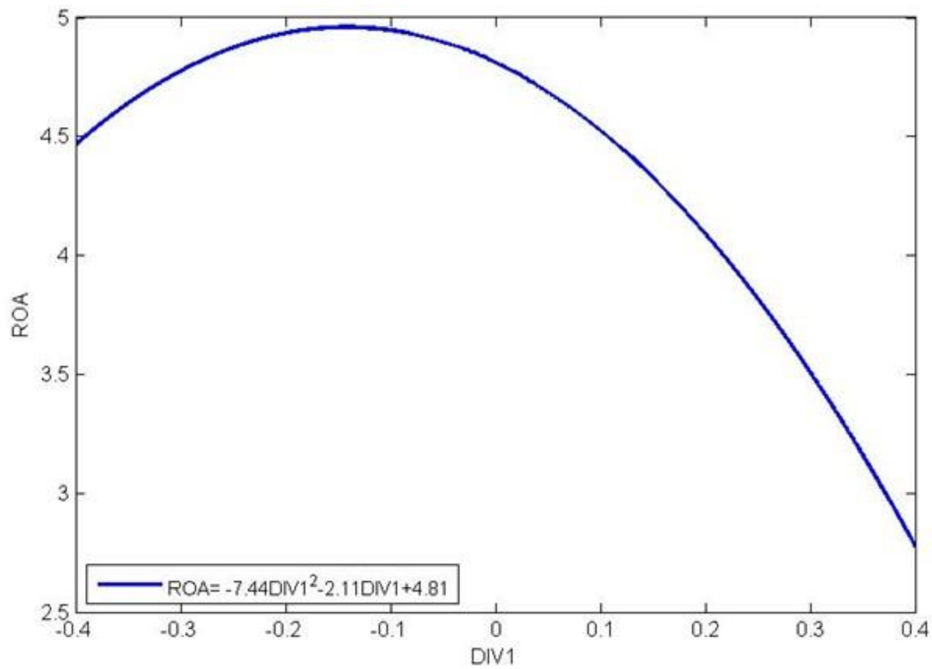


Figure 2. H'$_1$-Performance relationship at technology section level (mean-centered variables)

Table 4. Testing Hypothesis 2

	1	2	3	1	2	3	1	2	3
Direct effects									
H'_1	-1.84	-1.51	-1.98						
	(1.76)	(1.75)	(1.73)						
H'^{2}_{1}	-8.79***	-8.23***	-9.54***						
	(2.83)	(2.80)	(2.79)						
H'_2				-1.10	-1.13	-1.41			
				(1.11)	(1.11)	(1.12)			
H'^{2}_{2}				-1.72	-1.19	-1.42			
				(1.06)	(1.08)	(1.09)			
H'_3							2.16	2.06	1.89
							(1.61)	(1.61)	(1.61)
H'^{2}_{3}							2.26	2.27	1.9
							(1.17)	(1.16)	(1.20)
FCs	-0.18**	-0.12	0.09	-0.20**	-0.13	-0.05	-0.54**	-0.46	-0.35
	(0.09)	(0.09)	(0.11)	(0.09)	(0.09)	(0.11)	(0.16)	(0.17)	(0.19)
FCs^2	0.00	0.00	0.00	0.00	0.002*	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Linear mod.. effects									
H'_1x FCs		0.72***	0.40*						
		(0.22)	(0.24)						
H'_2x FCs					0.33**	0.2			
					(0.14)	(0.16)			
H'_3x FCs								0.30**	0.17
								(0.20)	(0.23)
Non-Linear mod. effects									
H'^{2}_{1}x FCs			-1.78***						
			(0.54)						
H'^{2}_{2}x FCs						-0.28			
						(0.18)			
H'^{2}_{3}x FCs									-0.26*
									(0.20)
Controls									
Dummy NAICS333	3.05**	3.58***	3.30***	2.82**	3.05**	3.04**	3.97	4.21*	4.27*
	(1.20)	(1.20)	(1.18)	(1.22)	(1.21)	(1.21)	(2.09)	(2.10)	(2.10)
Dummy NAICS335	0.91	1.02	1.17	0.40	0.03	0.27	3.18	2.66	3.23
	(1.81)	(1.78)	(1.76)	(1.81)	(1.80)	(1.81)	(3.32)	(3.34)	(3.36)
Multiplicity	-0.58	-0.47	-0.45	-0.31	-0.34	-0.31	-1.44	-1.58	-1.46
	(0.51)	(0.50)	(0.50)	(0.62)	(0.62)	(0.62)	(1.02)	(1.02)	(1.03)
Firm size	1.96***	2.05***	1.96***	1.98***	2.06***	2.08***	4.54***	4.58***	4.57***
	(0.40)	(0.40)	(0.39)	(0.41)	(0.41)	(0.41)	(0.73)	(0.73)	(0.73)
R&D expenditures	-0.04	-0.04	-0.05	-0.03	-0.02	-0.02	0.08	0.09	0.08
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.10)	(0.10)	(0.10)
Breadth sections	-0.2	-0.32	-0.30	-0.03	-0.02	-0.03	-0.03	-0.02	-0.02
	(0.46)	(0.45)	(0.45)	(0.06)	(0.06)	(0.06)	(0.03)	(0.03)	(0.03)
Intercept	-4.89**	-5.27**	-4.67**	-7.00***	-7.56***	-7.62***	-16.35***	-16.39***	-16.49***
	(2.05)	(2.03)	(2.01)	(2.23)	(2.23)	(2.22)	(4.29)	(4.28)	(4.28)
F-stat	6.76***	7.26***	7.76***	6.10***	6.14***	5.87***	11.37***	10.56***	9.84***
R^2	0.16	0.18	0.20	0.14	0.16	0.16	0.24	0.25	0.25
Δ F-stat	6.76***	10.51***	11.09***	6.10***	5.79**	2.52	11.37***	2.14**	1.66*
Adjusted-R^2	0.13	0.15	0.18	0.12	0.13	0.13	0.22	0.22	0.23
Sample size	376	376	376	377	377	377	370	370	370
Highest VIF	4.22	4.44	6.54	7.63	7.66	7.73	6.81	7.21	7.39

**p ≤ 0.1 **p ≤ 0.05 ***p ≤ 0.01*

All diversity indicators jack-knifed

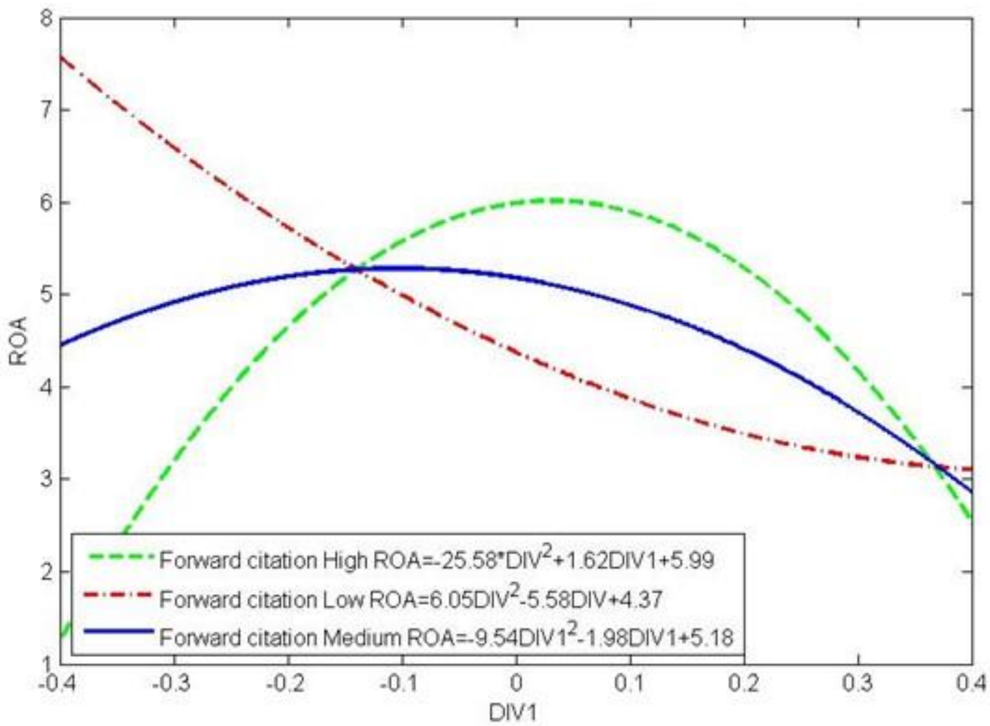


Figure 3. Moderating role of FCs in the relationship between H'_1 and firm profitability (mean-centered variables)

Table 5. Testing Hypothesis 3

	1	2	3	1	2	3	1	2	3
Direct effects									
H'$_1$	-2.42	-2.42	-2.02						
	(1.75)	(1.73)	(1.74)						
H'$_1^2$	-7.80***	-9.15***	-8.08***						
	(2.82)	(2.86)	(2.88)						
H'$_2$				-1.12	-1.46	-1.21			
				(1.13)	(1.13)	(1.13)			
H'$_2^2$				-1.96*	-2.12**	-1.83*			
				(1.07)	(1.06)	(1.06)			
H'$_3$							0.66	0.28	0.6
							(0.95)	(0.95)	(0.95)
H'$_3^2$							0.71	0.28	-0.01
							(0.67)	(0.69)	(0.68)
BCs	0.07	0.05	0.16*	0.00	-0.01	0.11	-0.03	-0.02	0.11
	(0.08)	(0.08)	(0.09)	(0.08)	(0.08)	(0.09)	(0.08)	(0.08)	(0.09)
BCs^2	-0.003**	-0.003*	-0.004**	0.00	0.00	0.00	0.00	0.00	-0.004***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Linear moderation. effects									
H'$_1$x BCs		0.43**	0.45***						
		(0.17)	(0.17)						
H'$_2$x BCs					0.28**	0.28***			
					(0.11)	(0.11)			
H'$_3$x BCs								0.26**	0.22**
								(0.10)	(0.10)
Non-Linear moderation. effects									
H'$_1^2$x BCs			-0.82**						
			(0.37)						
H'$_2^2$x BCs						-0.35**			
						(0.14)			
H'$_3^2$x BCs									-0.28***
									(0.09)
Controls									
Dummy NAICS333	3.29***	3.33***	3.19***	3.18**	2.85**	3.01**	2.34*	2.01*	2.37**
	(1.17)	(1.17)	(1.16)	(1.22)	(1.22)	(1.21)	(1.20)	(1.20)	(1.19)
Dummy NAICS335	0.60	0.37	0.54	0.32)	-0.35	-0.35	-0.09	-0.85	-0.52
	(1.80)	(1.79)	(1.78)	(1.84)	(1.85)	(1.83)	(1.85)	(1.86)	(1.85)
Multiplicity	-0.17	-0.15	-0.11	-0.15	-0.25	-0.17	0.14	-0.14	-0.05
	(0.53)	(0.33)	(0.53)	(0.64)	(0.63)	(0.63)	(0.59)	(0.59)	(0.59)
Firm size	1.66***	1.74***	1.70***	1.82***	1.87***	1.85***	1.71***	1.74***	1.72***
	(0.40)	(0.39)	(0.39)	(0.41)	(0.41)	(0.41)	(0.42)	(0.41)	(0.41)
R&D expenditures	-0.09	-0.09*	-0.09	-0.07	-0.06	-0.05	-0.05	-0.03	-0.02
	(0.46)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.02)	(0.06)	(0.06)
Breadth sections	-0.19	-0.26	-0.24	-0.02	0.00	-0.01	-0.02	-0.01	-0.01
	(0.46)	(0.46)	(0.45)	(0.06)	(0.06)	(0.06)	(0.02)	(0.02)	(0.02)
Intercept	-4.72**	-4.93**	-4.94**	-6.79***	-7.03***	-7.03***	-7.26***	-6.91***	-6.83***
	(2.02)	(2.01)	(2.00)	(2.25)	(2.22)	(2.22)	(2.45)	(2.43)	(2.41)
F-stat	5.66***	5.78***	5.76***	5.52***	5.71***	5.78***	5.02***	5.23***	5.69***
R^2	0.13	0.15	0.16	0.13	0.15	0.16	0.12	0.14	0.16
ΔF-stat	5.66***	6.17**	4.94**	5.52***	6.73**	5.757**	5.02***	6.53**	9.46**
Adjusted-R^2	0.11	0.12	0.13	0.11	0.12	0.13	0.1	0.11	0.13
Sample size	376	376	376	377	377	377	377	377	377
Highest VIF	4.49	4.49	4.49	7.66	7.78	7.84	6.96	8.01	8.11

$*p \leq 0.1$ $**p \leq 0.05$ $***p \leq 0.01$
All diversity indicators jack-knifed

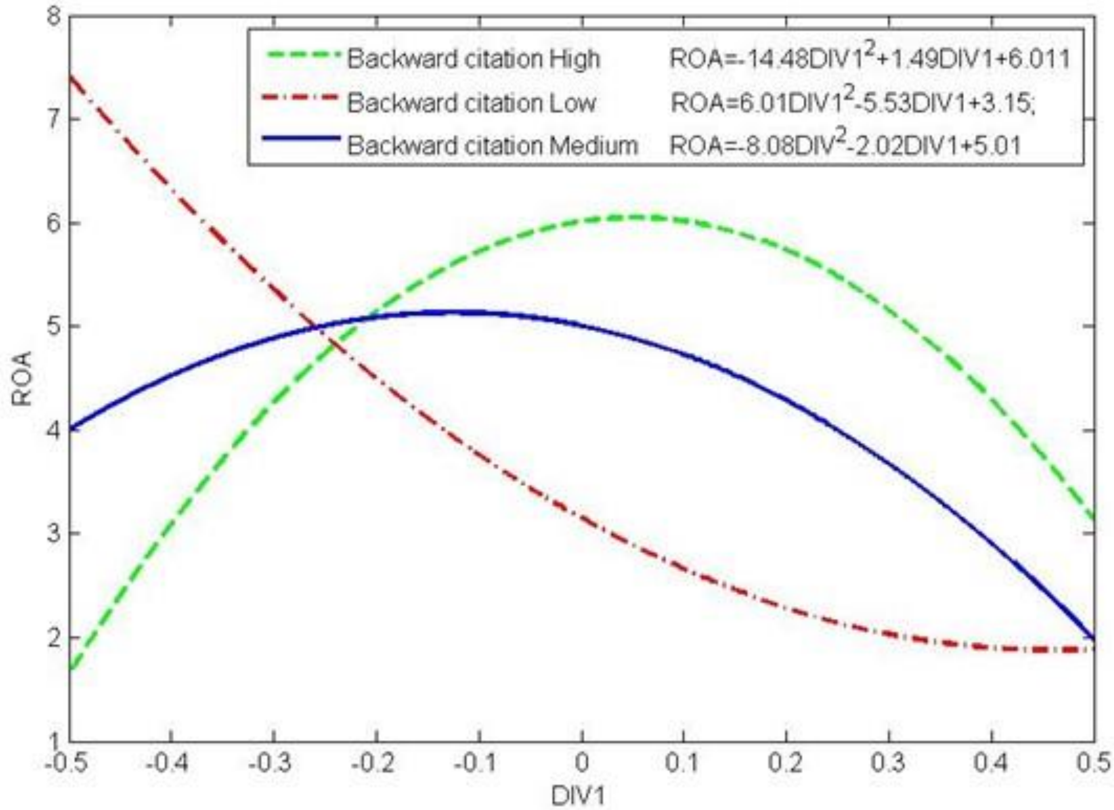


Figure 4. Moderating role of BCs in the relationship between $H'H_1$ and Profitability (mean-centered variables)

Table 6. Summary of results (considering other performance measures for robustness check)

Hypothesis 1

The relationship between diversity and profitability is curvilinear (inverted U-shaped) with the highest profitability occurring at an intermediate level of diversity.

		Robustness check		
	ROA	*Profit Margin*	*ROE*	*Cash Flow*
H'H$_1$	✓	✓	✓	*n.s*
H'H$_2$	n.s	*n.s*	*n.s*	✓
H'H$_3$	n.s	*n.s*	✗	*n.s*

Hypothesis 2

The number of non-self FCs moderates the inverted U-shape relationship between diversity and profitability: increasing the number of non-self FCs decreases the negative concavity of the curve.

	ROA	*Profit Margin*	*ROE*	*Cash Flow*
H'H$_1$	✗	✗	✗	*n.s*
H$_2$	n.s	✗	*n.s*	*n.s*
H$_3$	✗	✗	*n.s*	*n.s*

Hypothesis 3

The number of non-self BCs moderates the inverted U-shape relationship between diversity and profitability: increasing number of non-self BCs accentuates the negative concavity of the curve.

	ROA	*Profit Margin*	*ROE*	*Cash Flow*
H'H$_1$	✓	✓	✓	*n.s*
H'H$_2$	✓	✓	✓	*n.s*
H'H$_3$	✓	✓	✓	*n.s*

✓: results support the hypothesis; ✗ results are opposite to the hypothesis; n.s: non-significant results